CLAIMS

What is claimed is:

1. A method for providing a virtual age estimation for predicting the remaining lifetime of a device of a given type, comprising the steps of:

monitoring a predetermined number of significant parameters of respective ones of a training set of devices of said given type, said parameters contributing respective wear increments;

determining coefficients of a radial basis function neural network for modeling said wear increments from said training set operated to failure and whereof the respective virtual ages are normalized substantially to a desired norm value;

deriving from said radial basis function neural network a formula for virtual age of a device of said given type; and

applying said formula to said significant parameters from a further device of the said given type for deriving wear increments for said further device.

2. A method for providing a virtual age estimation as recited in claim 1, including a step of cumulating said further device so as to derive a virtual age estimation for said further device.

3. A method for providing a virtual age estimation as recited in claim 1, including a step of selecting said predetermined number of significant parameters by selecting a number thereof so as to minimize deviations of said virtual ages from said normalized virtual age.

4. A method for providing a virtual age estimation for devices of a given type by predicting the remaining lifetime of a further device of said given type by computing wear increments, comprising the steps of:

collecting data on parameters contributing wear increments in a training set of sample devices until failure, said sample devices being similar to said given device;

modeling a wear increment by a radial basis function neural network;

computing the sum of increments for individual sample devices in said training set to obtain a virtual age therefor, said virtual age being normalized substantially to a convenient normalized virtual age; and

determining coefficients of said radial basis function neural network in a supervised training phase of said sample devices in said training set for said normalized virtual age; and

deriving incremental wear data for a further device, similar to said sample devices, by utilizing device data for said further device in conjunction with said coefficients of said radial basis function neural network determined in the preceding step.

5. A method for providing a virtual age estimation for devices as recited in claim 4, including a step of cumulating said incremental wear data to derive a virtual age for said further device.

6. A method for providing a virtual age estimation for devices as recited in claim 4, wherein said step of determining coefficients of said radial basis function neural network comprises a step of optimizing said determining by utilizing Ridge regression.

7. A method for providing a virtual age estimation for devices as recited in claim 6, wherein said step utilizing Ridge regression includes a step of optimizing by cross validation between devices in a subset of said training set and the remainder of devices in said training set.

8. A method for providing a virtual age estimation for devices as recited in claim 6, wherein said step of determining coefficients of said radial basis function neural network includes a step of optimizing said coefficients for reducing deviations of said virtual ages from said normalized virtual age.

9. A method for providing a virtual age estimation for devices as recited in claim 6, wherein said step of optimizing said coefficients includes a step of minimizing the sum of least squares of said deviations.

10. A method for providing a virtual age estimation for devices by predicting the remaining lifetime of a given device by computing wear increments, comprising the steps of:

modeling wear increments by a radial basis function neural network based on selected wear parameters which contribute wear increments for said devices;

adjusting coefficients of said radial basis function neural network in accordance with data derived in a training set of such devices for deriving an equation for increments of virtual age for each device in said training set, said virtual ages being normalized substantially to a desired standard value; and

applying said equation to said selected wear parameters of a further device similar to devices in said training set for computing wear increments for said further device.

11. A method for providing a virtual age estimation for devices as recited in claim 10, including a step of cumulating said wear increments for said further device for computing a virtual age for said further device.

12. A method for providing a virtual age estimation for devices as recited in claim 10, wherein said step of determining coefficients of said radial basis function neural network comprises a step of optimizing said determining by utilizing Ridge regression.

13. A method for providing a virtual age estimation for devices as recited in claim 12, wherein said step utilizing Ridge regression includes a step of optimizing by cross validation between devices in a subset of said training set and the remainder of devices in said training set.

14. A method for providing a virtual age estimation for devices as recited in claim 10, wherein said step of determining coefficients of said multivariate radial basis function neural network includes a step of optimizing said coefficients for reducing deviations of said virtual ages from said normalized virtual age.

15. A method for providing a virtual age estimation for devices as recited in claim 14, wherein said step of optimizing said coefficients includes a step of minimizing the sum of least squares of said deviations.

16. Apparatus for providing a virtual age estimation for predicting the remaining lifetime of a device of a given type, comprising:

means for monitoring a predetermined number of significant parameters of respective ones of a training set of devices of said given type, said parameters contributing respective wear increments;

means for determining coefficients of a radial basis function neural network for modeling said wear increments determined from said training set operated to failure and whereof the respective virtual ages are normalized substantially to a desired norm value;

means for deriving from said radial basis function neural network a formula for virtual age of a device of said given type; and

means for applying said formula to said significant parameters from a further device of the said given type for deriving wear increments for said further device.

17. A method for providing a virtual age estimation for predicting the remaining lifetime of a device comprises the steps of:

monitoring a plurality of significant variable parameters of a device during active operation of said system;

selecting at least a subset of said plurality of significant variable parameters and forming therefrom a series of d-dimensional measurement vectors comprising scalars respectively corresponding to said at least a subset of said significant variable parameters;

deriving respective wear increments corresponding to said scalars;

modeling said wear increments by a radial basis function neural network with M hidden units, wherein M is a free parameter, resulting in a linear system of equations;

determining M coefficients in a supervised training phase involving N histories of devices which failed;

computing for each device the M independent sums over all wear increments, thereby obtaining an (N x M) matrix and *N* equations for the virtual age of each device; and

computing from said (N x M) matrix and *N* equations a virtual age for each device.

18. A method for providing a virtual age estimation as recited in claim 17, including a step of normalizing said virtual age with respect to a given number.

19. A method for providing a virtual age estimation as recited in claim 17, including a step of normalizing said virtual age with respect to unity.

20. A method for providing a virtual age estimation for predicting the remaining lifetime of a device comprises the steps of:

monitoring a plurality of significant variable parameters of a device during active operation of said system;

selecting at least a subset of said plurality of significant variable parameters and forming therefrom a series of d-dimensional measurement vectors comprising scalars respectively corresponding to said at least a subset of said significant variable parameters;

deriving respective wear increments corresponding to said scalars;

modeling said wear increments by a Gaussian basis function neural network with M hidden units, wherein M is a free parameter, resulting in a linear system of equations;

determining M coefficients in a supervised training phase involving N histories of devices which failed;

computing for each device the M independent sums over all wear increments, thereby obtaining an (N x M) matrix and *N* equations for the virtual age of each device; and

computing from said (N x M) matrix and *N* equations a virtual age for each device.

21. A method for providing a virtual age estimation as recited in claim 20, including a step of normalizing said virtual age with respect to a given number.

22. A method for providing a virtual age estimation as recited in claim 20 including a step of normalizing said virtual age with respect to unity.

23. A method for providing a virtual age estimation as recited in claim y wherein said step of modeling said wear increments by a Gaussian basis function comprises modeling by a function of the form

$$g(\bar{x},\bar{z},\sigma)=\exp\left(-\frac{\|\bar{x}-\bar{z}\|^2}{2\sigma^2}\right)$$

wherein $g(\bar{x},\bar{z},\sigma)$ represents the Gaussian basis function

$\bar{x},\bar{z}$, and σ respectively represent

24. A method for providing a virtual age estimation as recited in claim 23, including a step of selecting the z_i by applying a clustering algorithm to the measurement vectors

25. A method for providing a virtual age estimation as recited in claim 24, including a step of applying a a scale factor, whereby another free parameter λ is introduced, to be chosen via cross-validation, whereby σ_i transforms into $\lambda\sigma_i$.

26. A method for providing a virtual age estimation as recited in claim 20, including a step of normalizing said virtual age with respect to a given number.

27. A method for providing a virtual age estimation as recited in claim 20, including a step of normalizing said virtual age with respect to unity.

28. A method for providing a virtual age estimation as recited in claim 24, including a step of deriving σ_i by taking σ_i be a global constant.

29. A method for providing a virtual age estimation as recited in claim 24, including a step of deriving σ_i by taking σ_i be the average of the distance from each measurement to the first nearest measurement.

30. A method for providing a virtual age estimation as recited in claim 24, including a step of applying a a scale factor, whereby another free parameter λ is introduced, to be chosen via cross-validation, whereby σ_i transforms into $\lambda\sigma_i$.

31. A method for providing a virtual age estimation as recited in claim 30 including a step of normalizing said virtual age with respect to a given number.

32. A method for providing a virtual age estimation as recited in claim 31 including a step of normalizing said virtual age with respect to unity.

33. A method for providing a virtual age estimation as recited in claim 29, including a step of deriving σ_i by taking σ_i be the average of the distance from each measurement to the k'th nearest measurement.

34. A method for providing a virtual age estimation as recited in claim 29, including a step of applying a a scale factor, whereby another free parameter λ is introduced, to be chosen via cross-validation, whereby σ_i transforms into $\lambda\sigma_i$.

35. A method for providing a virtual age estimation as recited in claim 29, including a step of normalizing said virtual age with respect to a given number.

36. A method for providing a virtual age estimation as recited in claim 29, including a step of normalizing said virtual age with respect to unity.